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Term Project – Checkpoint C
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Introduction

With so many ETF's and Mutual Funds currently available, it's a massive market that many investors such as myself need to understand so that we can make our best judgement on which ones to invest in. It's no different then trying to buy a house and doing market comparisons and research on the house. According to ICI (Investment Company Institute) there are over 10,000 (Active and Index) Mutual Funds and ETF's with over $32,679 trillion of assets. With so many ETF's and Mutual funds, it's more important than ever to understand how they leverage modern day technologies to optimize portfolios, maximize returns, and reduce risks. Instead of going with the basic 5 assets as required by the assignment, I decided to expand my scope to 15 assets along a wide spectrum including index funds themselves. I also wanted to truly understand how our strategies that we're learning apply to modern day portfolios where it's a combination of equities, bonds, index funds, treasuries, etc. Most average investors gravitate towards the companies that make the news but there's still thousands of other assets that isn't in the news that help balance the ETF's and Mutual Funds.

Through quantitative finance and leveraging technology such as Python, it's now possible for average investors such as myself to be able to form my own investment portfolio of assets using the theories of quantitative finance and python. In the past, these two factors were limited to companies with scale, data, and teams of people. Now with improving pathetical models and technological advances, anyone can form their own portfolios.

Who else has conducted research like this?

While it would be any investors dream to invest in a company and hope that the company stock only goes up but that's not reality. As Markowitz (1952) points out that "if we ignore market imperfections the foregoing rule never implies that there is a diversified portfolio which is preferable to all non-diversified portfolios." Unfortunately, this is not reality. We've seen many downturns in the market that last days, weeks, months, and even years. According to Morningstar, from 1900's to 2000's there have been over 19 market crashes ranging from 19.6% to 79% decline. In Fundamental Indexation by Arnott, Hsu, and Moore (2005), they proved that their fundamental indexation strategy outperformed the S&P 500 by an average of 1.91% higher. Fundamental index investing is where a fund will re-balance the index fund portfolio based on financial measures of company size rather than stock price and serves as a complement to market-capitalization index strategies. Arnott, Hsu, and Moore re-balances their fund every year.

On momentum/trend, I build on Jegadeesh & Titman's seminal cross-sectional work and the broader evidence from Asness et al., Antonacci, D'Souza et al., and Gray, which show that simple trend rules can persist across assets and decades. On mean reversion, the signal construction follows the practitioner canon (Garner; Chen) and is consistent with the educational overview popularized by Algovibes. Combining momentum and mean-reversion tilts, as we do, echoes the “complementary edges” argument discussed by Velissaris.

How are you conducting the research?

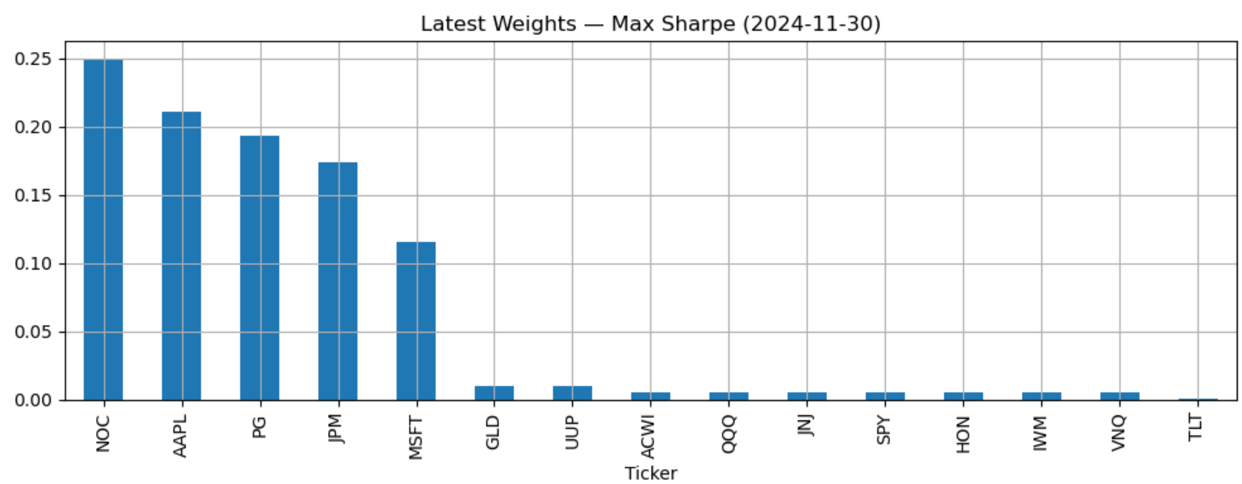
It’s not just the portfolios we hear about that are well balanced. According to Brinson, Singer, and Beebower (1991) 82 pension plans all had asset class weights for equity, bonds, cash, and “other” from 1977 to 1987. Their portfolio allocation was about 605 equity and 40% fixed income. Even in my role overseeing the Treasury team for my company and talking with OCIO’s about recommended investments for the company, they all recommended a diverse set of investments across equities, fixed income, cash, and alternatives. Looking at Morningstar’s most well balanced US-Focused Mutual Funds all include a healthy mix of equity, fixed income, and some cash. Since my portfolio comprise of index funds. ETF’s on the other hand are more equity based according to Morningstar’s Q2 Top Performing ETF’s. Since the hypothetical portfolio and 15 assets chosen are all equities / ETF’s, this portfolio operates more like a ETF. Within the portfolio, there are 7 traditional company stocks and 8 ETF’s.

Ticker	Name
AAPL	Apple Inc.
JPM	JPMorgan Chase & Co.
HON	Honeywell International Inc.
NOC	Northrop Grumman Corporation
MSFT	Microsoft Corporation
JNJ	Johnson & Johnson
PG	The Procter & Gamble Company
SPY	SPDR S&P 500 ETF Trust (tracks the S&P 500 index)
IWM	iShares Russell 2000 ETF (tracks the Russell 2000 index)
QQQ	Invesco QQQ Trust (tracks the Nasdaq-100 Index)
ACWI	iShares MSCI ACWI ETF (All Country World Index)
TLT	iShares 20+ Year Treasury Bond ETF (tracks the US Treasury with remaining maturities greater than 20 years)
GLD	SPDR Gold Shares (tracks the price performance of gold bullion)
VNQ	Vanguard Real Estate ETF (invests in stocks issued by REIT’s)
UUP	Invesco DB U.S. Dollar Index Bullish Fund (tracks US dollar)

The company equities cover a wide variety of industries that include technology, financial services, industries, defense, healthcare, and consumer products. The ETF’s in the portfolio cover broad indexes.

Exploratory data analysis establishes start/end dates, annualized return and volatility, rolling Sharpe, drawdowns, and cross-asset correlations. Using Python, we compute two simple, orthogonal signals: a 12-month momentum measure and a mean-reversion z-score relative to a rolling mean/vol. From there, we can then blend them into a modest tilt on expected returns before optimization. Portfolio construction is based on long-only and compares four allocators: Max Sharpe, Min Variance, Risk Parity (inverse-vol), and Max Return and is subject to realistic constraints: per-asset caps on UUP/TLT/GLD of 1% each and small floors so every live asset receives some allocation at each rebalance. In the initial model without any constraints, GLD, UUP portfolio optimization weights were increased due to it's low volatility which helped maximized the sharpe ratio. This method proved to actually not be able to beat the benchmark S&P 500 returns over time. Instead, we set max constraints in on those index funds to limit exposure to those funds given it's lower annual returns and a minimum floor so that every asset receives some allocation.

	Start	End	Years	CAGR	AnnMu	AnnVol
Asset						
AAPL	1999-01-31	2024-12-31	25.916496	0.295049	0.340858	0.387864
JPM	1999-01-31	2024-12-31	25.916496	0.092039	0.133360	0.298114
HON	1999-01-31	2024-12-31	25.916496	0.096247	0.132855	0.281983
NOC	1999-01-31	2024-12-31	25.916496	0.141955	0.159980	0.230665
MSFT	1999-01-31	2024-12-31	25.916496	0.112319	0.146783	0.283823
JNJ	1999-01-31	2024-12-31	25.916496	0.074961	0.086930	0.169860
PG	1999-01-31	2024-12-31	25.916496	0.079001	0.092970	0.178381
SPY	1999-01-31	2024-12-31	25.916496	0.079764	0.088627	0.151864
IWM	2000-05-31	2024-12-31	24.585900	0.078487	0.096500	0.202168
QQQ	1999-03-31	2024-12-31	25.754962	0.099774	0.123513	0.234674
ACWI	2008-03-31	2024-12-31	16.752909	0.073894	0.086079	0.169484
TLT	2002-07-31	2024-12-31	22.420260	0.037157	0.045833	0.136974
GLD	2004-11-30	2024-12-31	20.084873	0.086922	0.097425	0.166598
VNQ	2004-09-30	2024-12-31	20.251882	0.073948	0.096694	0.220414
UUP	2007-03-31	2024-12-31	17.754962	0.018655	0.021506	0.077717



What did you learn from your research so far?

As I was modeling the different asset classes across 25 years, one of the biggest pain points that I encountered was trying to do portfolio optimization back all those years. The challenge was some of the ETF's were not available until mid to late 2000's. This created complexity since the data was not available. I could have gone the easy route and done equal-weighting portfolio methodology but that's not optimal to maximizing returns and reducing risks. According to Markowitz, investors "should diversify and that they should maximize expected returns."

I learned that portfolio optimization doesn't just mean trying to make a mathematical model work. Unfortunately, it's not as simple since in the initial model without any minimum or maximum weight constraints the three assets that I had selected to include in the portfolio: GLD, UUP, and TLT initially drove the weighting of the portfolio significantly. While this increased the max sharpe ratio, this reduced the overall expected return. After adding the constraints, the portfolio's expected return was then able to come close to beating the S&P 500 benchmark.

	CAGR	AnnVol	Sharpe	Alpha(ann)	Beta	MaxDD	Calmar
BENCH	0.107330	0.148044	0.724985	0.000000	1.000000	-0.507848	0.211342
60_40	0.084567	0.099161	0.852833	0.023145	0.559726	-0.284526	0.297222
EW_LIVE	0.131666	0.120589	1.091857	0.044100	0.779212	-0.373061	0.352933
MAX_SHARPE_NET	0.102839	0.139172	0.738929	0.019086	0.785103	-0.515985	0.199305
MIN_VAR_NET	0.076402	0.125302	0.609744	-0.002276	0.741097	-0.467915	0.163283
RISK_PARITY_NET	0.102607	0.139338	0.736385	0.004826	0.908664	-0.482056	0.212852
MAX_RETURN_NET	0.125882	0.164603	0.764763	0.026218	0.941550	-0.538888	0.233596

- CAGR: compound annual growth rate (annualized return). 0.1073 ≈ 10.73%/yr.
- AnnVol: annualized volatility (standard deviation of returns). Higher = more bumpy ride.
- Sharpe: return per unit of risk (here, excess return over ~0 risk-free divided by AnnVol). Bigger is better.
- Alpha (ann): annualized excess return vs SPY after adjusting for beta (roughly: what the strategy adds beyond what its market exposure would explain).
- Beta: sensitivity to SPY (≈1 moves like the market; <1 is more defensive).
- MaxDD: worst peak-to-trough loss on the equity curve (e.g., -0.5078 = -50.8%).
- Calmar: drawdown-aware efficiency = CAGR / |MaxDD|. Higher means more return per unit of pain.

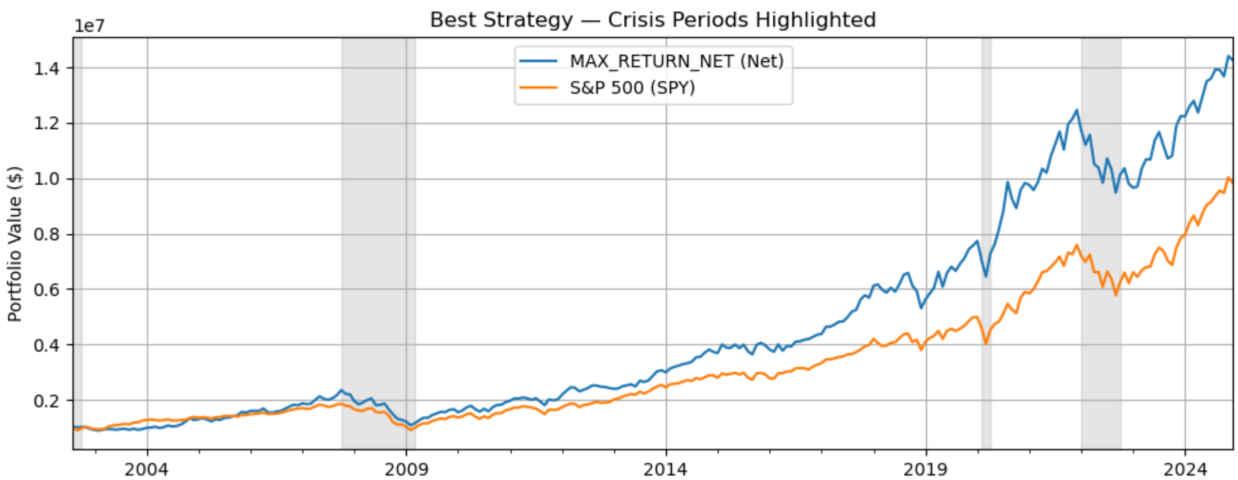
Surprisingly though the model with the best overall metrics was the equal-weight model with a CAGR 13.17%, vol 12.06%, Sharpe 1.09 (best), alpha +4.41%/yr, max DD -37.3%, Calmar 0.353 (best).

While the equal weights did have the best overall metrics, that was not a computed model so for the backtesting, I went with the MAX_RETURN_NET model.

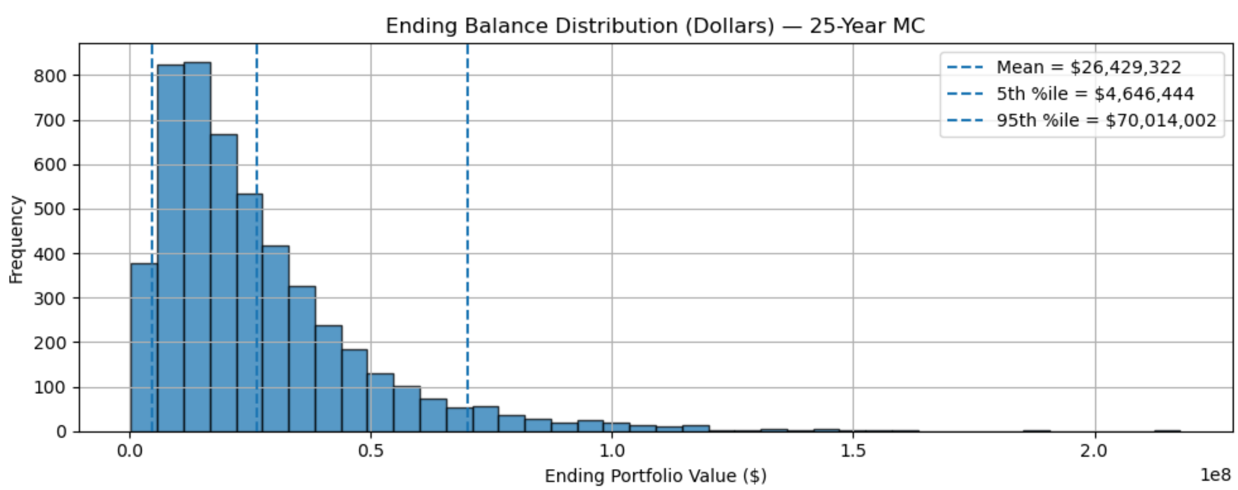
So, what does it all mean?

The research delivers a reproducible, defensible investment process that produces net-of-fees, benchmarked outcomes and analytics. With conservative, long-only constraints and explicit fee and turnover modeling, the strategy's risk-adjusted profile looks competitive, and the stress-test evidence suggests controlled drawdowns relative to a simple SPY hold. The Monte Carlo results translate those properties into investor-friendly dollar outcomes and probabilistic ROI, which is precisely what prospective investors are looking for.

The portfolio was then compared against stress/crisis periods in the market to see how it would do against benchmark. For most stress/crisis periods, the portfolio performed in line or slightly better than the S&P 500 benchmark.



Assuming a $1M initial investment in the portfolio, we can expect the portfolio to generate a net return of ~$26M in 25 years.



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